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OIL, UNCERTAINTY, AND GASOLINE PRICES

Dongfeng Chang
Shandong University

Apostolos Serletis
University of Calgary

In this paper we investigate the relationship between crude oil and gasoline prices and also examine the effect of oil price uncertainty on gasoline prices. The empirical model is based on a structural vector autoregression that is modified to accommodate multivariate GARCH-in-Mean errors. We use monthly data for the United States over the period from January 1976 to September 2014. We find that there is an asymmetric relationship between crude oil and gasoline prices, and that oil price uncertainty has a positive effect on gasoline price changes. Our results are robust to alternative model specifications and alternative measures of the price of oil.

Keywords: Oil Price Volatility, GARCH-in-Mean VAR

1. INTRODUCTION

The typical consumer of gasoline believes that gasoline prices respond faster and by more to positive oil price shocks than to negative ones. As Duffy-Deno (1996, p. 81) puts it, "in response to higher crude oil prices and, hence, higher wholesale prices, retail (pump) prices rise quickly and completely. But when wholesale prices decline, retail prices fall at a much slower rate and may not fully adjust to the lower wholesale price environment." This asymmetric relationship is described by Bacon (1991) as "rockets and feathers"—in the sense that gasoline prices rise rapidly like rockets in response to crude oil price increases, but fall slowly like feathers in response to crude oil price declines. The public seems to treat the asymmetric relationship between crude oil and gasoline prices as evidence of a noncompetitive petroleum market, which would suggest government intervention to prevent "unfair pricing"—see discussions by Brown and Yücel (2000). On the other hand, no policy response is required if gasoline prices respond symmetrically to crude oil price changes.

A number of theoretical studies have attempted to investigate the asymmetric relationship between crude oil and gasoline prices, with a variety of explanations,

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TABLE 1. Summary of previous empirical studies for the United States

Author(s)	Model used	Data used	Asymmetry found
Karrenbrock (1991)	Distributed lag model	Monthly, 1983–1990	Yes
Duffy-Deno (1996)	First differences	Weekly, 1989–1993	Yes
Borenstein et al. (1997)	ECM	Weekly and biweekly, 1986–1992	Yes
Balke et al. (1998)	VAR and ECM	Weekly, 1987–1997	Mixed
Akarca and Andrianacos (1998)	Linear regression	Monthly, 1976–1996	Yes
Borenstein and Shepard (2002)	VAR and partial adjustment	Weekly, 1986–1992	Yes
Johnson (2002)	ECM	Weekly, 1996–1998	Yes
Bachmeier and Griffin (2003)	ECM	Daily, 1985–1998	No
Davis and Hamilton (2004)	ACH, asymmetric logit	Daily, 1989-1991	Yes
Radchenko (2005)	VAR and ECM	Weekly, 1991–2003	Yes
Kaufmann and Laskowski (2005)	ECM	Monthly, 1986–2002	Yes
Radchenko and Shapiro (2011)	VAR	Weekly, 1991–2010	Yes

including adjustment of production and inventory cost of crude oil, oligopolistic coordination theory, and search theory—see, for example, Borenstein et al. (1997) and Peltzman (2000). In the empirical literature, the "rockets and feathers" behavior has mostly been investigated using monthly or weekly data to check the speed of pass-through from oil price changes to gasoline price changes and the asymmetry in the responses to positive and negative oil price shocks. With the exception of Davis and Hamilton (2004) and Douglas and Herrera (2010), most papers employ a vector autoregression (VAR) model or an error correction model (ECM) with homoskedastic disturbances to test for asymmetry in the parameters of the mean equation, as can be seen in Table 1, which lists a number of studies using data for the United States. Although the relationship between gasoline and crude oil prices has been extensively investigated, there is no consensus on whether the relationship is symmetric or asymmetric, although the majority of studies conclude in favor of an asymmetric relationship (as can be seen in Table 1).

In this paper we examine the relationship between crude oil and retail gasoline prices using recent advances in financial econometrics and macroeconometrics. In doing so, we use a structural VAR that is modified to accommodate bivariate GARCH-in-Mean errors, allowing us to directly investigate the effect of oil price uncertainty on gasoline prices. We use monthly data for the United States, over the period from January 1976 to September 2014, obtained from the Energy

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Information Administration, and estimate the model using full information maximum likelihood, avoiding Pagan's (1984) generated regressor problems. We conduct impulse-response analysis to investigate whether the relationship between crude oil and gasoline prices is symmetric or asymmetric. We also investigate the robustness of our results to alternative measures of the price of oil and alternative model specifications.

Our principal result is that the relationship between crude oil and gasoline prices is asymmetric, consistent with the consensus opinion based on models different from ours. We also investigate the effects of uncertainty about the price of oil on the price of gasoline. As a measure of oil price uncertainty, we use the conditional standard deviation of the forecast error for the change in the price of oil. We find that uncertainty about the price of oil has a positive and statistically significant effect on the price of gasoline and that accounting for oil price uncertainty tends to change the estimated response of gasoline prices to oil price shocks. Our results are robust to alternative measures of the price of oil and alternative model specifications.

The outline of the paper is as follows. Section 2 presents the bivariate GARCH-in-Mean structural VAR that we use to investigate the direct effects of oil price uncertainty on the price of gasoline and the relationship between gasoline and crude oil prices. Section 3 discusses the data and investigates their time series properties. Section 4 presents the main empirical results regarding the asymmetric relationship between gasoline and crude oil prices and the positive and significant effect of oil price uncertainty on the price of gasoline. In Section 5 we investigate the robustness of our results to the use of real prices, two alternative oil price series, a bivariate GARCH-in-Mean BEKK model, and a formal symmetry test based on a nonlinear structural VAR, recently proposed by Kilian and Vigfusson (2011). The final section briefly concludes the paper.

2. THE STRUCTURAL GARCH-IN-MEAN VAR

Our empirical model was developed in Elder (2004) to investigate the effects of inflation uncertainty. It has also been used by Elder and Serletis (2010) to investigate the effects of oil price shocks and oil price uncertainty on the level of real economic activity. It is a bivariate structural VAR, modified to accommodate GARCH-in-Mean errors.

We specify the vector $\boldsymbol{z}_t$ to include the change in the logged price of oil, o_t, and the change in the logged price of gasoline prices, g_t. We assume the conditional mean model

$$\boldsymbol{B}\boldsymbol{z}_t = \boldsymbol{C} + \sum_{j=1}^{p} \Gamma^j \boldsymbol{z}_{t-j} + \Lambda \sqrt{\boldsymbol{h}_t} + \boldsymbol{e}_t, \tag{1}$$

$$\boldsymbol{e}_t \,|\, \Omega_{t-1} \sim (\boldsymbol{0}, \boldsymbol{H}_t), \quad \boldsymbol{H}_t = \begin{bmatrix} h_{\mathrm{oo},t} & h_{\mathrm{og},t} \\ h_{\mathrm{og},t} & h_{\mathrm{gg},t} \end{bmatrix},$$

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where

$$\boldsymbol{z}_t = \begin{bmatrix} o_t \\ \\ g_t \end{bmatrix}; \boldsymbol{e}_t = \begin{bmatrix} e_{o,t} \\ \\ e_{g,t} \end{bmatrix};$$

$$\Gamma^j = \begin{bmatrix} \gamma_{11}^j & \gamma_{12}^j \\ \\ \gamma_{21}^j & \gamma_{22}^j \end{bmatrix}; \Lambda = \begin{bmatrix} \lambda_{11} & 0 \\ \\ \lambda_{21} & 0 \end{bmatrix}, \boldsymbol{h}_t = \begin{bmatrix} h_{\mathrm{oo},t} \\ \\ h_{\mathrm{gg},t} \end{bmatrix},$$

and Ω_{t-1} denotes the information set at time $t-1$, which includes variables dated $t-1$ and earlier. As can be seen, we allow the vector of conditional standard deviations, $\sqrt{\boldsymbol{h}_t}$, to affect the conditional mean.

We specify the following equation for the conditional covariance matrix $\boldsymbol{H}_t$:

$$\mathrm{diag}(\boldsymbol{H}_t) = \boldsymbol{C}^v + \sum_{j=1}^{r} \boldsymbol{F}_j \mathrm{diag}\left(\boldsymbol{e}_{t-j}\boldsymbol{e}'_{t-j}\right) + \sum_{i=1}^{s} \boldsymbol{G}_i \mathrm{diag}\left(\boldsymbol{H}_{t-i}\right), \qquad (2)$$

where diag is the operator that extracts the diagonal from a square matrix. We impose the additional restriction that the conditional variances depend only on their own past squared errors and their own past conditional variances, so that the parameter matrices $\boldsymbol{F}_j$ and $\boldsymbol{G}_i$ are also diagonal. In fact, to deal with estimation problems in the large parameter space, we estimate the variance function (2) with $r = s = 1$. As can be seen from (1), the model allows contemporaneous oil price volatility, $\sqrt{h_{\mathrm{oo},t}}$, to affect the change in the logged gasoline price by the coefficient λ_{21}.

The system is identified by assuming that the diagonal elements of the contemporaneous coefficient matrix $\boldsymbol{B}$ are unity, that $\boldsymbol{B}$ is lower triangular, and that the structural disturbances are contemporaneously uncorrelated (that is, the conditional covariance matrix, $\boldsymbol{H}_t$, is diagonal). The parameters are estimated by full information maximum likelihood, avoiding the generated regressor problems associated with estimating the variance function parameters separately from the conditional mean parameters. In particular, we use the estimation procedure described in Elder (2004), in which the bivariate GARCH-in-Mean VAR, equations (1) and (2), is estimated by full information maximum likelihood by numerically maximizing the log likelihood function,

$$l_t = -\frac{n}{2}\ln(2\pi) + \frac{1}{2}\ln|\boldsymbol{B}|^2 - \frac{1}{2}\ln|\boldsymbol{H}_t| - \frac{1}{2}\left(\boldsymbol{e}_t^{'}\boldsymbol{H}_t^{-1}\boldsymbol{e}_t\right),$$

with respect to the structural parameters $\boldsymbol{B}$, $\boldsymbol{C}$, Γ, Λ, $\boldsymbol{C}^v$, $\boldsymbol{F}$, and $\boldsymbol{G}$.

In doing so, we set the presample values of the conditional variance matrix $\boldsymbol{H}_0$ to their unconditional expectation and condition on the presample values of $\boldsymbol{z}_t$. To ensure that $\boldsymbol{H}_t$ is positive definite, we restrict $\boldsymbol{C}^v > 0$, $\boldsymbol{F} \geq 0$, and $\boldsymbol{G} \geq 0$, as in Engel and Kroner (1995). Provided that the standard regularity conditions are satisfied, full information maximum likelihood estimates are asymptotically

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TABLE 2. Unit root and stationarity tests

	Unit root tests			KPSS tests	
Variable	ADF (level)	ADF (trend)	ADF	Level	Trend
o_t	−11.142	−11.131	−11.099	0.061	0.051
g_t	−11.936	−11.923	−11.850	0.039	0.039
5% critical value	−2.868	−3.421	−1.940	0.463	0.146

Note: Sample period, monthly data: 1976:2–2014:9.

normal and efficient, with the asymptotic covariance matrix given by the inverse of Fisher's information matrix. See Elder (2004) or Elder and Serletis (2010) for more details.

3. THE DATA

We use the U.S. refiners' acquisition cost (RAC) for a composite of domestic and imported crude oil as a proxy for the price of oil, and the U.S. average retail price for regular unleaded gasoline, including taxes, as a proxy for the retail price of gasoline. Both prices were obtained from the Energy Information Administration on a monthly basis over the period from January 1976 to September 2014 and are in nominal terms. The refiners' acquisition cost for composite crude oil is a weighted average of domestic and imported crude oil costs and includes transportation and other fees paid by refiners, but does not include the cost of crude oil purchased for the Strategic Petroleum Reserve.

Using the retail price of gasoline inclusive of taxes could have been problematic if there had been any significant tax fluctuations over the sample period. However, the tax remained unchanged for several years at a time and tax changes occurred only four times over our sample period—in 1983 with a 5 cent increase per gallon; in 1987 with a 0.1 cent increase per gallon; in 1990 with a 5 cent increase per gallon; and in 1993 with a 4.3 cent increase per gallon. We ignore the impact of these fuel tax changes in this study.

Although many homoskedastic VARs are estimated using variables in the levels, we estimate our GARCH-in-Mean structural VAR using logarithmic first differences of the nominal crude oil and gasoline prices. In fact, we begin by checking the stationarity of both series using augmented Dickey–Fuller (ADF) unit root tests [see Dickey and Fuller (1981)] as well as KPSS tests for level and trend [see Kwiatkowski et al. (1992)]. The results of these tests are reported in Table 2 and show that the null hypothesis of a unit root can be rejected at 5% level. Moreover, the KPSS t-statistics for level and trend stationarity are small relative to their 5% critical values. Hence, we conclude that the first logged differences of the crude oil and gasoline prices, o_t and g_t, are stationary.

Next we conduct Ljung–Box Q tests for serial correlation in each of the o_t and g_t series. The Q-statistic is asymptotically distributed as a $\chi^2(36)$ on the null

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TABLE 3. Serial correlation and ARCH tests

Variable	$Q(2)$	$Q(4)$	ARCH (1)
o_t	131.934 (0.000)	137.018 (0.000)	0.658 (0.000)
g_t	95.622 (0.000)	104.738 (0.000)	0.676 (0.000)

Notes: Sample period, monthly data: 1976:2–2014:9. p-values are in parentheses.

of no autocorrelation. The Q tests are reported in Table 3 and show that there is significant serial dependence in both series. In Table 3 we also report Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) χ^2 test, distributed as a $\chi^2(1)$ on the null hypothesis of no ARCH. The test indicates that there is strong evidence of conditional heteroskedasticity in both series.

4. EMPIRICAL EVIDENCE

We estimate the bivariate GARCH-in-Mean structural VAR, equations (1) and (2), with two lags as suggested by the Schwarz (1978) information criterion (SIC), using monthly observations on the logarithmic first differences of nominal crude oil and gasoline prices over the period from 1976:4 to 2014:9 (a total of 462 observations). To ensure that our specification is consistent with the data, we calculate the SIC for the conventional homoskedastic VAR and the bivariate GARCH-in-Mean VAR. The Schwarz criterion includes a substantive penalty for the additional parameters required to estimate GARCH models, and so an improvement in the SIC suggests strong evidence in favor of our specification. The SIC value for the structural GARCH-in-Mean VAR is −3,400, considerably lower than that for the conventional homoskedastic VAR of −3,122, meaning that our GARCH-in-Mean VAR captures important features of the data.

The point estimates of the variance function parameters of the GARCH-in-Mean VAR [that is, equation (2)] are reported in panel B of Table 4 (under nominal prices) and provide further support for our specification. In particular, there is statistically significant evidence of both ARCH and GARCH effects in both crude oil and gasoline prices. In fact, at a monthly frequency, the volatility process for the price of oil and also that for the price of gasoline are very persistent, as the sums of the ARCH and GARCH coefficients are $(0.336 + 0.634 =)$ 0.970 and $(0.179 + 0.796 =)$ 0.975, respectively. Another coefficient of interest relates to the effect of crude oil price uncertainty on the price of gasoline. This is the coefficient on the conditional standard deviation of the change in the logged oil price in the gasoline price equation, λ_{21}. It is reported as the last entry in panel A of Table 4 (under nominal prices) and is positive and equal to 0.064 with a p-value of 0.039, meaning that higher crude oil price uncertainty tends to increase the change in the logged price of gasoline in a statistically significant way over our sample period.

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TABLE 4. Coefficient estimates for the bivariate GARCH-in-Mean VAR, equations (1) and (2), with nominal and real prices

Coefficient	Nominal prices	Real prices
	A. Mean equation	
b	−0.274 (0.000)	−0.249 (0.000)
c_1	0.653 (0.000)	0.636 (0.000)
γ_{11}^1	−0.129 (0.042)	−0.117 (0.052)
γ_{12}^1	−0.222 (0.001)	−0.232 (0.001)
γ_{21}^1	0.030 (0.659)	0.034 (0.625)
γ_{22}^1	0.001 (0.914)	−0.003 (0.560)
λ_{11}	0.067 (0.606)	0.099 (0.443)
c_2	0.099 (0.000)	0.108 (0.000)
γ_{11}^2	−0.062 (0.018)	−0.060 (0.018)
γ_{12}^2	0.473 (0.000)	0.475 (0.000)
γ_{21}^2	−0.205 (0.000)	−0.220 (0.000)
γ_{22}^2	0.000 (0.948)	−0.002 (0.185)
λ_{21}	0.064 (0.039)	0.074 (0.013)
	B. Variance equation	
c_1^v	0.000 (0.000)	0.000 (0.000)
f_{11}	0.336 (0.000)	0.339 (0.000)
g_{11}	0.634 (0.000)	0.633 (0.000)
c_2^v	0.000 (0.000)	0.000 (0.000)
f_{22}	0.179 (0.000)	0.180 (0.000)
g_{22}	0.796 (0.000)	0.794 (0.000)

Note: Sample period, monthly data: 1976:2–2014:9. Numbers in parentheses are p-values.

To assess the effect of incorporating oil price uncertainty on the dynamic response of gasoline prices to an oil price shock, we plot the associated impulse responses in Figures 1 and 2 for small positive and negative oil price shocks (one-standard-deviation shocks) and in Figures 3 and 4 for big oil price shocks (two-standard-deviation shocks). The impulse responses are based on an oil price shock equal to the annualized unconditional standard deviation of the change in the price of oil and are calculated as in Elder (2003), using the Monte Carlo method to construct the confidence bands as described in Hamilton (1994, p. 337). That is, the impulse responses are simulated from the maximum likelihood estimates of the model's parameters and one-standard-error bands are generated by simulating 1,000 impulse responses, based on parameter values drawn randomly from the sampling distribution of the maximum likelihood parameter estimates, where the covariance matrix of the maximum likelihood estimates is derived from an estimate of Fisher's information matrix.

Figure 1 shows the impulse response of the price of gasoline to small (one-standard-deviation) positive oil price shocks. The response indicates that,

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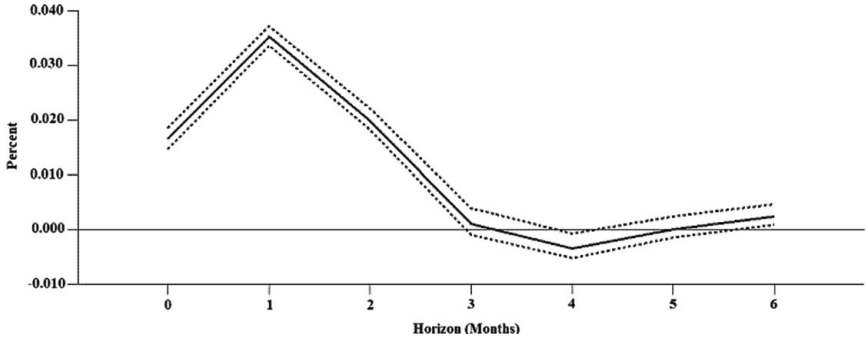


FIGURE 1. Gasoline price response to one-standard-deviation positive oil price shocks.

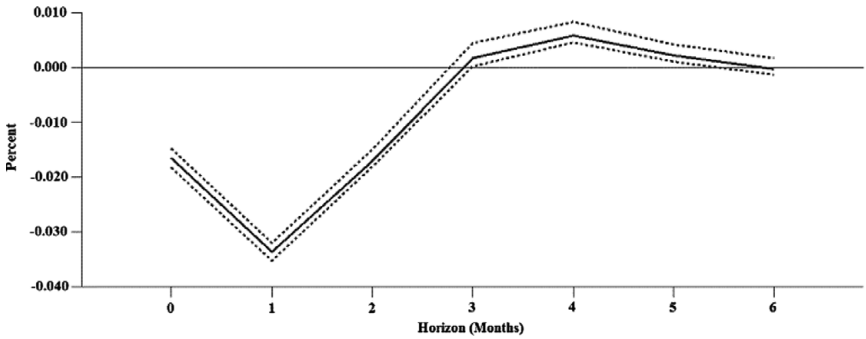


FIGURE 2. Gasoline price response to one-standard-deviation negative oil price shocks.

accounting for the effects of oil price uncertainty, a small positive oil price shock tends to increase the price of gasoline immediately, inducing a jump in its monthly rate of change of about 3.6 basis points after one month, followed by a decline in the second month by about 2 basis points. The dynamic effect of the positive oil price shock on the price of gasoline is also statistically significant for the first two months, as the response of the price of gasoline is well within one standard error of zero. This result is consistent with Bacon (1991), who reports similar evidence for the United Kingdom. In Figure 2 we report the impulse response of the price of gasoline to small negative oil price shocks, again accounting for the effects of oil price uncertainty. As can be seen, a small negative oil price shock tends to have a statistically significant effect on the price of gasoline, reducing its change by about 3.3 basis points after one month and increasing it by about 1.7 basis points after two months. A visual comparison of the impulse responses in Figures 1 and 2 suggests that the response of the price of gasoline to small positive and negative oil price shocks is likely to be asymmetric.

In Figures 3 and 4 we show the impulse responses of the price of gasoline to big (two standard deviation) positive and negative oil price shocks, respectively, in the

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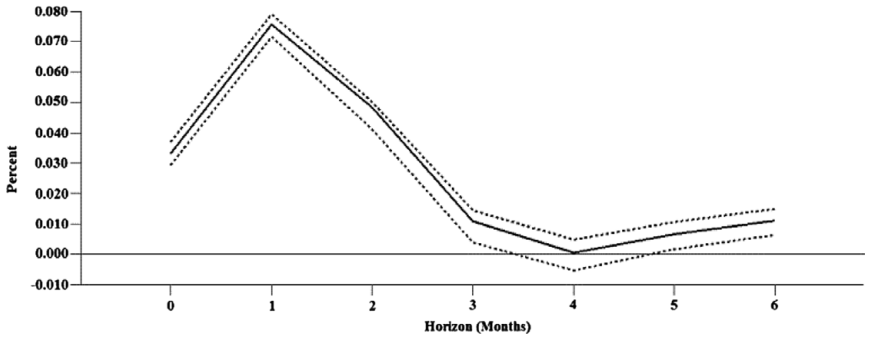


FIGURE 3. Gasoline price response to two-standard-deviation positive oil price shocks.

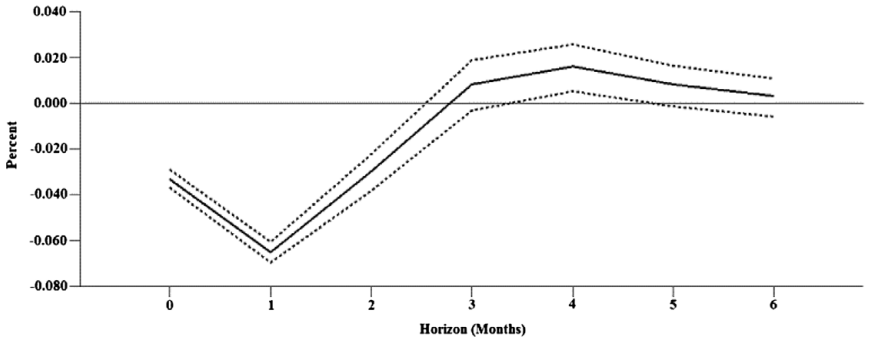


FIGURE 4. Gasoline price response to two-standard-deviation negative oil price shocks.

same fashion as those for small shocks in Figures 1 and 2. Again accounting for the effects of oil price uncertainty, in Figure 3 we find that large positive oil price shocks have positive and statistically significant effects on the price of gasoline. In particular, a two-standard-deviation positive oil price shock tends to increase the price of gasoline immediately, inducing a jump in its change rate of about 7.5 basis points after one month, followed by a decline in the second month by about 4.8 basis points. The impulse response of the gasoline price to large negative oil price shocks is shown in Figure 4 and indicates that large negative oil price shocks have negative and statistically significant effects, immediately reducing the price of gasoline by about 6.5 basis points after one month. In fact, we find that the price of gasoline responds more to positive oil shocks than to negative ones, irrespective of their size, and that the positive effects of large positive oil price shocks on the price of gasoline last longer than the negative effects of big negative oil price shocks.

Next, we compare the response of the price of gasoline to a small positive oil shock as estimated by our model [equations (1) and (2)] with that from a model in which oil price uncertainty is restricted from entering the gasoline price

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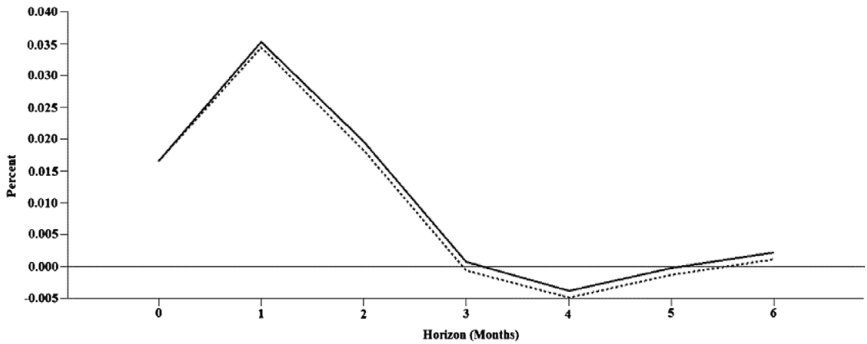


FIGURE 5. Gasoline price response to one-standard-deviation positive oil price shocks with $\lambda_{21} \neq 0$ (solid line) and $\lambda_{21} = 0$ (dashed line).

equation—that is, from a model with $\lambda_{21} = 0$. In Figure 5, the solid line represents the response of the price of gasoline to a small positive oil price shock in our model that accounts for oil price uncertainty (this is the same as the solid line in Figure 1; the error bands have been suppressed for clarity) and the dashed line represents the response of the price of gasoline to a small positive oil price shock when oil price uncertainty is restricted from entering the gasoline price equation (that is, when $\lambda_{21} = 0$). As shown in the figure, oil price uncertainty enhances the positive dynamic response of the price of gasoline to a positive oil price shock.

Finally, we can quantify the effect of oil price uncertainty on the gasoline price by using the estimated effect of oil price uncertainty on the price of gasoline for realistic changes in the standard deviation of the change in the price of oil. For example, the estimated effect of oil price uncertainty on the change of the price of gasoline is 0.064. The standard deviation of the change in the price of oil is 0.088. Therefore, the effect of a one-standard-deviation oil price shock on the change in the monthly price of gasoline is $0.064 \times 0.088 = 0.563\%$.

5. ROBUSTNESS

5.1. Real Prices

In this section we investigate the robustness of our results to the use of real prices. We obtain real prices by dividing each of the crude oil and gasoline prices by the U.S. consumer price index. We report the estimation results in the last column of Table 4, exactly in the same fashion as for those in the first column with the nominal prices. Again, the estimates of the variance function parameters (shown in panel B of Table 4, under real prices) indicate statistically significant ARCH and GARCH effects for both the real price of oil and the real price of gasoline. Moreover, in panel A of Table 4 (under real prices), we see that the coefficient on oil price uncertainty is positive ($\widehat{\lambda}_{21} = 0.074$) and statistically significant at the 5% level, consistent with our earlier result, based on the use of nominal prices.

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5.2. A GARCH-in-Mean BEKK VAR

We have used a structural VAR with GARCH-in-Mean errors. In this section we investigate the robustness of our results regarding the effects of oil price uncertainty on gasoline prices using a bivariate GARCH-in-Mean VAR with a BEKK(1,1,1) variance specification, as in Engle and Kroner (1995).

The mean equation is

$$\boldsymbol{z}_t = \mathbf{a} + \sum_{j=1}^{p} \Gamma^j \boldsymbol{z}_{t-j} + \Psi\sqrt{\boldsymbol{h}_t} + \boldsymbol{e}_t, \tag{3}$$

$$\boldsymbol{e}_t | \, \Omega_{t-1} \sim (\mathbf{0}, \boldsymbol{H}_t), \qquad \boldsymbol{H}_t = \begin{bmatrix} h_{\mathrm{oo},t} & h_{\mathrm{og},t} \\ h_{\mathrm{og},t} & h_{\mathrm{gg},t} \end{bmatrix},$$

where Ω_{t-1} denotes the available information set in period $t-1$, $\mathbf{0}$ is the null vector, and

$$\boldsymbol{z}_t = \begin{bmatrix} o_t \\ g_t \end{bmatrix}; \boldsymbol{e}_t = \begin{bmatrix} e_{o,t} \\ e_{g,t} \end{bmatrix}; \boldsymbol{h}_t = \begin{bmatrix} h_{\mathrm{oo},t} \\ h_{\mathrm{gg},t} \end{bmatrix};$$

$$\Gamma^j = \begin{bmatrix} \gamma_{11}^j & \gamma_{12}^j \\ \gamma_{21}^j & \gamma_{22}^j \end{bmatrix}; \Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}.$$

The variance equation is

$$\boldsymbol{H}_t = \boldsymbol{C}'\boldsymbol{C} + \boldsymbol{B}'\boldsymbol{H}_{t-1}\boldsymbol{B} + \boldsymbol{A}'\boldsymbol{e}_{t-1}\boldsymbol{e}_{t-1}'\boldsymbol{A}, \tag{4}$$

where $\boldsymbol{C}$, $\boldsymbol{A}$, and $\boldsymbol{B}$ are 2×2 parameter matrices and $\boldsymbol{C}$ is upper triangular, ensuring positive definiteness of the conditional covariance matrix $\boldsymbol{H}_t$. For more details regarding this model, see Rahman and Serletis (2011).

In the context of this model, consisting of equations (3) and (4), the primary coefficient of interest is ψ_{21}—the coefficient of $\sqrt{h_{\mathrm{oo},t}}$ in the mean equation (3). It relates to the effect of oil price uncertainty on gasoline prices.

The estimated value of ψ_{21} is 0.423 with a p-value of 0.028. This is positive and statistically significant at the 5% level, consistent with the evidence based on the structural model, equations (1) and (2).

5.3. A Statistical Test of Symmetric Impulse Responses

We have argued that the impulse response functions based on the bivariate structural model with GARCH-in-Mean errors, equations (1) and (2), indicate an asymmetric relationship between crude oil prices and gasoline prices. To investigate the robustness of this result, we use an impulse-response-based test, recently proposed by Kilian and Vigfusson (2011). The Kilian and Vigfusson symmetry test, based on

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impulse response functions, involves estimating the following nonlinear structural VAR model:

$$o_t = \alpha_{10} + \sum_{j=1}^{p} \beta_{11}(j) o_{t-j} + \sum_{j=1}^{p} \beta_{12}(j) g_{t-j} + u_{1t},$$

$$g_t = \alpha_{20} + \sum_{j=0}^{p} \beta_{21}(j) o_{t-j} + \sum_{j=1}^{p} \beta_{22}(j) g_{t-j} + \sum_{j=0}^{p} \delta_{21}(j) \tilde{o}_{t-j} + u_{2t},$$

where $\tilde{o}_t$ is Hamilton's (2003) net oil price increase over the previous six months, defined as

$$\tilde{o}_t = \max\left[0, \ln \text{Oil}_t - \max\left\{\ln \text{Oil}_{t-1}, \ln \text{Oil}_{t-2}, ..., \ln \text{Oil}_{t-6}\right\}\right],$$

where Oil denotes the price of oil.

The null hypothesis of symmetric impulse responses of g_t to positive and negative oil price shocks of the same size is

$$H_0 : I_g(h, \delta) = -I_g(h, -\delta) \quad \text{for } h = 0, 1, ..., H. \tag{5}$$

It tests whether the response of g_t to a positive shock in the oil price growth rate of size δ is equal to the negative of the response of g_t to a negative shock in the oil price growth rate of the same size, $-\delta$, for horizons $h = 0, 1, ..., H$. For a detailed discussion of the methodology, see Kilian and Vigfusson (2011).

Because the Kilian and Vigfusson (2011) test depends on the size of the shock, δ, in Figure 6 we show the empirical responses of the change in the logged gasoline price to one- and two-standard-deviation positive and negative oil price shocks, in a model with two lags and including the six-month net oil price increase. In particular, the figure plots the response of the change in the logged gasoline price to a positive shock, $I_g(h, \delta)$, and the negative of the response to a negative shock, $-I_g(h, -\delta)$. The impulse responses are derived for six months based on 10,000 simulations and 50 histories.

As can be seen in Figure 6, the response of the change in the logged gasoline price to positive shocks is larger than that to negative shocks for both small (one-standard-deviation) and large (two-standard-deviation) oil price shocks. Moreover, in panel *A* of Table 5, we report *p*-values of the null hypothesis (5) for both small shocks ($\delta = \hat{\sigma}$) and large shocks ($\delta = 2\hat{\sigma}$). As can be seen, we generally reject the null hypothesis of a symmetric relationship between gasoline prices and crude oil prices at the 5% significance level.

5.4. Other Oil Prices

We have used the refiners' acquisition cost for a composite of domestic and imported crude oil as a proxy for the price of oil. There are, however, other candidates for the oil price series, including the refiners' acquisition cost for imported crude oil, the refiners' acquisition cost for domestic crude oil, the price

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TABLE 5. p-values for $H_0 : I_g(h, \delta) = -I_g(h, -\delta)$, $h = 0, 1, ..., 6$

	RAC of crude oil					
	A. Composite		B. Domestic		C. Imported	
h	$\widehat{\sigma}$	$2\widehat{\sigma}$	$\widehat{\sigma}$	$2\widehat{\sigma}$	$\widehat{\sigma}$	$2\widehat{\sigma}$
0	0.343	0.021	0.711	0.072	0.319	0.018
1	0.072	0.025	0.010	0.190	0.023	0.019
2	0.019	0.000	0.008	0.038	0.005	0.000
3	0.036	0.000	0.000	0.030	0.007	0.000
4	0.012	0.000	0.000	0.045	0.003	0.000
5	0.019	0.001	0.000	0.075	0.006	0.000
6	0.032	0.002	0.000	0.113	0.011	0.001

Note: p-values are based on the χ^2_{h+1} distribution.

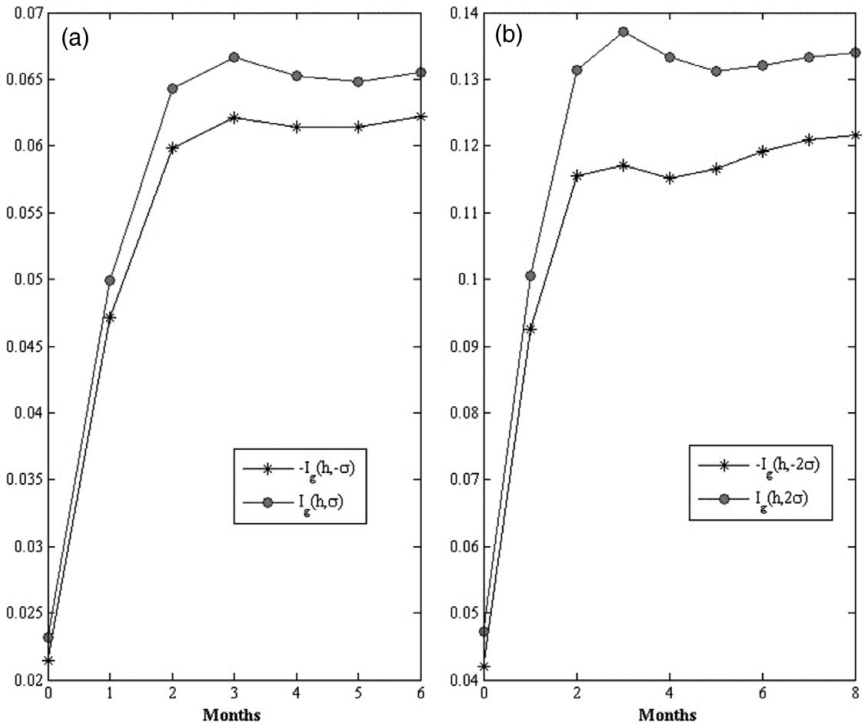


FIGURE 6. (a) Gasoline price response to one-standard-deviation oil shocks. (b) Gasoline price response to two-standard-deviation oil shocks.

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TABLE 6. Volatility estimates based on equations (1) and (2)

Crude oil price	SIC lag	$\widehat{\lambda}_{21}$	p-value
Nominal RAC Composite	2	0.064	0.039
Nominal RAC Domestic	2	0.069	0.000
Nominal RAC Imported	2	0.039	0.000

Note: Sample period, monthly data: 1976:2–2014:9.

of West Texas Intermediate crude oil, and the U.S. producer price of crude oil. We believe that for the purpose of investigating the relationship between the price of crude oil and the retail price of gasoline (and consistent with the gasoline production chain in the United States), the refiners' acquisition cost for crude oil is the most appropriate price of oil to use.

However, in this section we investigate the robustness of our results to the use of the refiners' acquisition cost for domestic crude oil and the refiners' acquisition cost for imported crude oil. In panels B and C of Table 5, we report p-values of the null hypothesis (5) with the RAC Domestic and RAC Imported oil series, respectively, in the same fashion as in panel A with the RAC Composite. We report results for both small shocks (one-standard-deviation shocks, $\delta = \hat{\sigma}$) and large shocks (two-standard-deviation shocks, $\delta = 2\hat{\sigma}$). In general, we reject the null hypothesis of symmetric impulse responses, consistent with our earlier conclusion.

We also investigate the robustness of our results regarding the effects of oil price uncertainty on the price of gasoline to the use of the refiners' acquisition cost for domestic crude oil and the refiners' acquisition cost for imported crude oil. As reported in Table 6, the effect of oil price uncertainty on the change in the logged gasoline price is positive and statistically significant at the 5% level when the RAC Domestic is used as the price of oil—$\widehat{\lambda}_{21} = 0.069$ with a p-value of 0.000. Moreover, the effect of oil price uncertainty on the price of gasoline is also statistically significant but smaller when the RAC Imported is used as the oil price (in this case, $\widehat{\lambda}_{21} = 0.039$ with a p-value of 0.000). We report volatility estimates in Table 7 based on the GARCH-in-Mean BEKK model. As can be seen, the effect of oil price uncertainty on the price of gasoline is positive, but no longer statistically significant, when the RAC Domestic and the RAC Imported are used as the price of oil. Specifically, $\widehat{\psi}_{21} = 0.113$ with a p-value of 0.602 when the RAC Domestic is used and $\widehat{\psi}_{21} = 0.116$ with a p-value of 0.225 when the RAC Imported is used.

6. CONCLUSION

We examine the relationship between crude oil and gasoline prices in the context of a structural VAR that is modified to accommodate bivariate GARCH-in-Mean errors. We estimate the model using full information maximum likelihood, avoiding Pagan's (1984) generated regressor problems, and conduct impulse-response

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TABLE 7. Volatility estimates based on equations (3) and (4)

Crude oil price	SIC lag	$\widehat{\psi}_{21}$	p-value
Nominal RAC Composite	2	0.423	0.028
Nominal RAC Domestic	2	0.113	0.602
Nominal RAC Imported	4	0.116	0.225

Note: Sample period, monthly data: 1976:2–2014:9.

analysis to investigate whether the relationship between crude oil and gasoline prices is symmetric or asymmetric. Using monthly data for the United States (from January 1976 to September 2014), we find an asymmetric relationship, consistent with the consensus opinion in the empirical literature. We also investigate the effects of uncertainty about the price of oil on the price of gasoline and find that oil price uncertainty has a positive and statistically significant effect on the price of gasoline. Our results are robust to alternative measures of the price of oil and alternative model specifications.

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